capstone_project

December 1, 2025

1 Adult Census Income Data Analysis

By Brandon Cabrera

This analysis is based on the Adult Census Income Data https://www.kaggle.com/datasets/uciml/adult-census-income/data

2 Adult Census Income Data Columns

The Adult Census Income data has 15 columns:

1. age: Age of the individual
2. workclass: Type of employment
3. fnlwgt: Indicates how many people the observation represents from the U.S. population
4. education: Highest level of education the indvdual completed
5. education.num: Numerical representation of education level
6. marital.status: Marital status of the individual
7. occupation: Occupation the individual holds
8. relationship: Relationship within the household
9. race: Race of the individual
10. sex: Biological sex
11. capital.gain: money earned from investments
12. capital.loss: money lost from investments
13. hours.per.week: Average number of hours worked per week
14. native.country: Country of origin
15. income: Indicates whether individual's income is > 50k or <= 50k

3 Analysis Questions

Throughout this analysis I will try to answer the following questions:

1. What was the average number of hours worked for a person who made > 50k, and what was the average number of hours worked for a person who made <= to 50k?
2. For a person whose highest education level is only high school, who makes > 50k, if any, what is the average number of hours worked?
3. What is the average education level for a person making > 50k, and what is the average education level for a person making <= 50k?
4. What is the correlation between capital gain and whether or not a person makes over 50k?
5. What marital status has the most people making over 50k, and what marital status has the most people making less than or equal to 50k?
6. What numerical column has the highest amount of correlation, in terms of magnitude, with whether or not a person made > 50k and whether they make <= to 50k?
7. What workclass has the most people making <= 50k, and what work class has the most people making > 50k?
8. Do women or men tend to make > 50k more than the other, and do women or men tend to make <= 50k?
9. What is the average age of men who make > 50k, and what is the average age of women who make > 50k?
10. Which race tends to make > 50k, more than the other races, and what race tends to make <= 50k more than the other races?

4 Importing Required Libraries

Before we start loading the data we need to import important libraries

[2]:
```
print("Done By Brandon Cabrera")
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
sns.set_theme()
```

```
Done By Brandon Cabrera
```

5 Importing Dataset

All of our data is contained within one dataset so let's load it and save it as a DataFrame

[3]:
```
print("Done By Brandon Cabrera")
adult_census_data = pd.read_csv('data/adult_census_income.csv') #load the csv␣
 ↪file into DataFrame
adult_census_data.head() # Display the first 5 rows of the dataset
```

```
Done By Brandon Cabrera
```

```
[3]:    age workclass  fnlwgt     education  education.num marital.status  \
     0   90         ?   77053       HS-grad              9        Widowed
     1   82   Private  132870       HS-grad              9        Widowed
     2   66         ?  186061  Some-college             10        Widowed
     3   54   Private  140359       7th-8th              4       Divorced
     4   41   Private  264663  Some-college             10      Separated

              occupation   relationship   race     sex  capital.gain  \
     0                 ?  Not-in-family  White  Female             0
     1   Exec-managerial  Not-in-family  White  Female             0
     2                 ?      Unmarried  Black  Female             0
     3 Machine-op-inspct      Unmarried  White  Female             0
     4    Prof-specialty      Own-child  White  Female             0

        capital.loss  hours.per.week native.country income
     0          4356              40  United-States  <=50K
     1          4356              18  United-States  <=50K
     2          4356              40  United-States  <=50K
     3          3900              40  United-States  <=50K
     4          3900              40  United-States  <=50K
```

Let's get some info about the columns of the dataset including how many non-null values they have and what each respective column's data type is.

```
[4]: print("Done By Brandon Cabrera")
     adult_census_data.info() #display the columns, non-null count, and data type
```

```
Done By Brandon Cabrera
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32561 non-null  int64
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64
 3   education       32561 non-null  object
 4   education.num   32561 non-null  int64
 5   marital.status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital.gain    32561 non-null  int64
 11  capital.loss    32561 non-null  int64
 12  hours.per.week  32561 non-null  int64
 13  native.country  32561 non-null  object
 14  income          32561 non-null  object
```

```
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

6 Cleaning and preparing dataset

Before starting to explore the dataset more in detail, let's make sure the dataset is clean, so let's check to see if there are any null values.

[5]:
```
print(adult_census_data.isnull().sum()) # creates a boolean mask of the
↪DataFrame then sum up the amount of True values(null values)
print("Done By Brandon Cabrera")
```

```
age               0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
capital.gain      0
capital.loss      0
hours.per.week    0
native.country    0
income            0
dtype: int64
Done By Brandon Cabrera
```

It appears there isn't an null values at first glace. However the dataset does contain '?' in some columns , e.g. row 0 of the workclass column contains a '?'. A question mark is a bit ambigious so for the sake of less ambiguity let's replace the question marks for NaN. So now the data set does have null values which be dealt with later on

[6]:
```
print("Done By Brandon Cabrera")
adult_census_data.replace('?', np.nan, inplace=True) # every '?' value will be
↪replaced for NaN
adult_census_data.head(10) # display first 10 rows
```

```
Done By Brandon Cabrera
```

[6]:

	age	workclass	fnlwgt	education	education.num	marital.status	\
0	90	NaN	77053	HS-grad	9	Widowed	
1	82	Private	132870	HS-grad	9	Widowed	
2	66	NaN	186061	Some-college	10	Widowed	
3	54	Private	140359	7th-8th	4	Divorced	
4	41	Private	264663	Some-college	10	Separated	
5	34	Private	216864	HS-grad	9	Divorced	

```
6   38       Private  150601          10th              6      Separated
7   74     State-gov   88638     Doctorate             16  Never-married
8   68   Federal-gov  422013       HS-grad              9       Divorced
9   41       Private   70037  Some-college             10  Never-married

          occupation    relationship   race     sex  capital.gain  \
0                NaN   Not-in-family  White  Female             0
1    Exec-managerial   Not-in-family  White  Female             0
2                NaN       Unmarried  Black  Female             0
3  Machine-op-inspct       Unmarried  White  Female             0
4     Prof-specialty       Own-child  White  Female             0
5      Other-service       Unmarried  White  Female             0
6       Adm-clerical       Unmarried  White    Male             0
7     Prof-specialty  Other-relative  White  Female             0
8     Prof-specialty   Not-in-family  White  Female             0
9       Craft-repair       Unmarried  White    Male             0

   capital.loss  hours.per.week native.country income
0          4356              40  United-States  <=50K
1          4356              18  United-States  <=50K
2          4356              40  United-States  <=50K
3          3900              40  United-States  <=50K
4          3900              40  United-States  <=50K
5          3770              45  United-States  <=50K
6          3770              40  United-States  <=50K
7          3683              20  United-States   >50K
8          3683              40  United-States  <=50K
9          3004              60            NaN   >50K
```

[7]:
```python
print("Done By Brandon Cabrera")
adult_census_data.tail(10) # display the last 10 rows
```

```
Done By Brandon Cabrera
```

[7]:
```
       age         workclass  fnlwgt     education  education.num  \
32551   43  Self-emp-not-inc   27242  Some-college             10
32552   32           Private   34066          10th              6
32553   43           Private   84661     Assoc-voc             11
32554   32           Private  116138       Masters             14
32555   53           Private  321865       Masters             14
32556   22           Private  310152  Some-college             10
32557   27           Private  257302    Assoc-acdm             12
32558   40           Private  154374       HS-grad              9
32559   58           Private  151910       HS-grad              9
32560   22           Private  201490       HS-grad              9

           marital.status         occupation   relationship  \
32551  Married-civ-spouse       Craft-repair        Husband
```

```
32552  Married-civ-spouse  Handlers-cleaners        Husband
32553  Married-civ-spouse              Sales        Husband
32554       Never-married       Tech-support  Not-in-family
32555  Married-civ-spouse    Exec-managerial        Husband
32556       Never-married    Protective-serv  Not-in-family
32557  Married-civ-spouse       Tech-support           Wife
32558  Married-civ-spouse  Machine-op-inspct        Husband
32559             Widowed       Adm-clerical      Unmarried
32560       Never-married       Adm-clerical      Own-child

                     race     sex  capital.gain  capital.loss  hours.per.week  \
32551               White    Male             0             0              50
32552  Amer-Indian-Eskimo    Male             0             0              40
32553               White    Male             0             0              45
32554  Asian-Pac-Islander    Male             0             0              11
32555               White    Male             0             0              40
32556               White    Male             0             0              40
32557               White  Female             0             0              38
32558               White    Male             0             0              40
32559               White  Female             0             0              40
32560               White    Male             0             0              20

      native.country income
32551  United-States  <=50K
32552  United-States  <=50K
32553  United-States  <=50K
32554         Taiwan  <=50K
32555  United-States   >50K
32556  United-States  <=50K
32557  United-States  <=50K
32558  United-States   >50K
32559  United-States  <=50K
32560  United-States  <=50K
```

Let's see how many null values we have now after replacing the '?' values.

[8]:
```python
print("Done By Brandon Cabrera")
print(adult_census_data.isnull().sum()) # creates a boolean mask of the
 ↪DataFrame then sum up the amount of True values(null values)
```

```
Done By Brandon Cabrera
age                  0
workclass         1836
fnlwgt               0
education            0
education.num        0
marital.status       0
occupation        1843
```

```
relationship         0
race                 0
sex                  0
capital.gain         0
capital.loss         0
hours.per.week       0
native.country     583
income               0
dtype: int64
```

Notice that the missing values are only for qualitative features and that all of the numeric features don't have any missing values. This sheds some light on why originally there were '?' values for these columns instead of NaN, because it's a qualitative column, and NaN isn't the most appropriate placeholder. For a better understanding of how many null values, let's have a look at the percentage of null values there is.

[9]:
```
print("Done By Brandon Cabrera")
print(((adult_census_data.isnull().sum() / len(adult_census_data)) * 100).
 ↪round(2)) # divide null values by total number of values in column and round␣
 ↪to two decimals
```

```
Done By Brandon Cabrera
age               0.00
workclass         5.64
fnlwgt            0.00
education         0.00
education.num     0.00
marital.status    0.00
occupation        5.66
relationship      0.00
race              0.00
sex               0.00
capital.gain      0.00
capital.loss      0.00
hours.per.week    0.00
native.country    1.79
income            0.00
dtype: float64
```

The highest percentage is in the occupation column, meaning 5.66 % of the values in the feature are null values. The percentage isn't that high, so we can get rid of the rows with null values without worrying about losing too much data.

[10]:
```
print("Done By Brandon Cabrera")
adult_census_data.dropna(inplace = True)
adult_census_data.count()
```

```
Done By Brandon Cabrera
```

[10]:
```
age               30162
workclass         30162
fnlwgt            30162
education         30162
education.num     30162
marital.status    30162
occupation        30162
relationship      30162
race              30162
sex               30162
capital.gain      30162
capital.loss      30162
hours.per.week    30162
native.country    30162
income            30162
dtype: int64
```

The null values in the dataset have been removed. I now want to add two binary columns using the 'income' column. One column will represent if the individual makes over 50k, and the other column will represent if the individiual makes less than or equal to 50k.

[11]:
```python
print("Done By Brandon Cabrera")
def add_income_binary_columns(df:pd.DataFrame) -> pd.DataFrame:
  """Adds two binary columns based on the income column to DataFrame passed as␣
↪an argument. One column represents if the individual makes
  > $50k and the other column represents whether the individual makes <= 50k.

  Args:
      df (DataFrame): DataFrame to add columns to

  Returns:
      DataFrame: Returns a DataFrame with the original columns and two new␣
↪binary columns
  """

  df['binary_income_over_$50k']  = (adult_census_data['income'] == '>50K').
↪astype(int) # 1 for over 50k and 0 for <= 50k
  df['binary_income_equal_under_$50k'] = (adult_census_data['income'] ==␣
↪'<=50K').astype(int) # 1 for <= 50k and 0 for > 50k
  return df
```

```
Done By Brandon Cabrera
```

Let's add the columns and then confirm that the two new columns were added.

[12]:
```python
print("Done By Brandon Cabrera")
adult_census_data = add_income_binary_columns(adult_census_data)
```

```
adult_census_data[['binary_income_over_$50k',␣
↪'binary_income_equal_under_$50k']].head(10) # display first 10 rows
```

```
Done By Brandon Cabrera
```

[12]:

	binary_income_over_$50k	binary_income_equal_under_$50k
1	0	1
3	0	1
4	0	1
5	0	1
6	0	1
7	1	0
8	0	1
10	1	0
11	1	0
12	1	0

We are going to drop 'fnlwgt' column since it doesn't provide us any useful information to help answer our questions

[13]:

```
print("Done By Brandon Cabrera")
adult_census_data.drop('fnlwgt', inplace = True, axis = 1)
```

```
Done By Brandon Cabrera
```

[14]:

```
print("Done By Brandon Cabrera")
adult_census_data.head()
```

```
Done By Brandon Cabrera
```

[14]:

```
   age workclass     education  education.num marital.status  \
1   82   Private       HS-grad              9        Widowed
3   54   Private       7th-8th              4       Divorced
4   41   Private  Some-college             10      Separated
5   34   Private       HS-grad              9       Divorced
6   38   Private          10th              6      Separated

          occupation   relationship   race     sex  capital.gain  \
1    Exec-managerial  Not-in-family  White  Female             0
3  Machine-op-inspct      Unmarried  White  Female             0
4     Prof-specialty      Own-child  White  Female             0
5      Other-service      Unmarried  White  Female             0
6       Adm-clerical      Unmarried  White    Male             0

   capital.loss  hours.per.week native.country income  \
1          4356              18  United-States  <=50K
3          3900              40  United-States  <=50K
4          3900              40  United-States  <=50K
5          3770              45  United-States  <=50K
```

```
6          3770             40   United-States   <=50K

   binary_income_over_$50k  binary_income_equal_under_$50k
1                        0                               1
3                        0                               1
4                        0                               1
5                        0                               1
6                        0                               1
```

7 Exploratory Data Analysis(EDA)

The exploration can be split up into two categories: numerical columns and qualitative columns. Our goal here is to get some graphs that help answer our analysis questions.

7.1 Exploring numerical columns

We're going to do some boxplots for our numerical columns as the y-values for our boxplots, and then for our x-values we'll do one of the binary income columns. It doesn't matter which of the two columns we choose since we'll still get the same information, the graphs would just be mirrored versions of each other.

[15]:
```
print("Done by Brandon Cabrera")
adult_census_data.select_dtypes(include='number').columns # show all of our␣
↪numeric columns
```

```
Done by Brandon Cabrera
```

[15]:
```
Index(['age', 'education.num', 'capital.gain', 'capital.loss',
       'hours.per.week', 'binary_income_over_$50k',
       'binary_income_equal_under_$50k'],
      dtype='object')
```

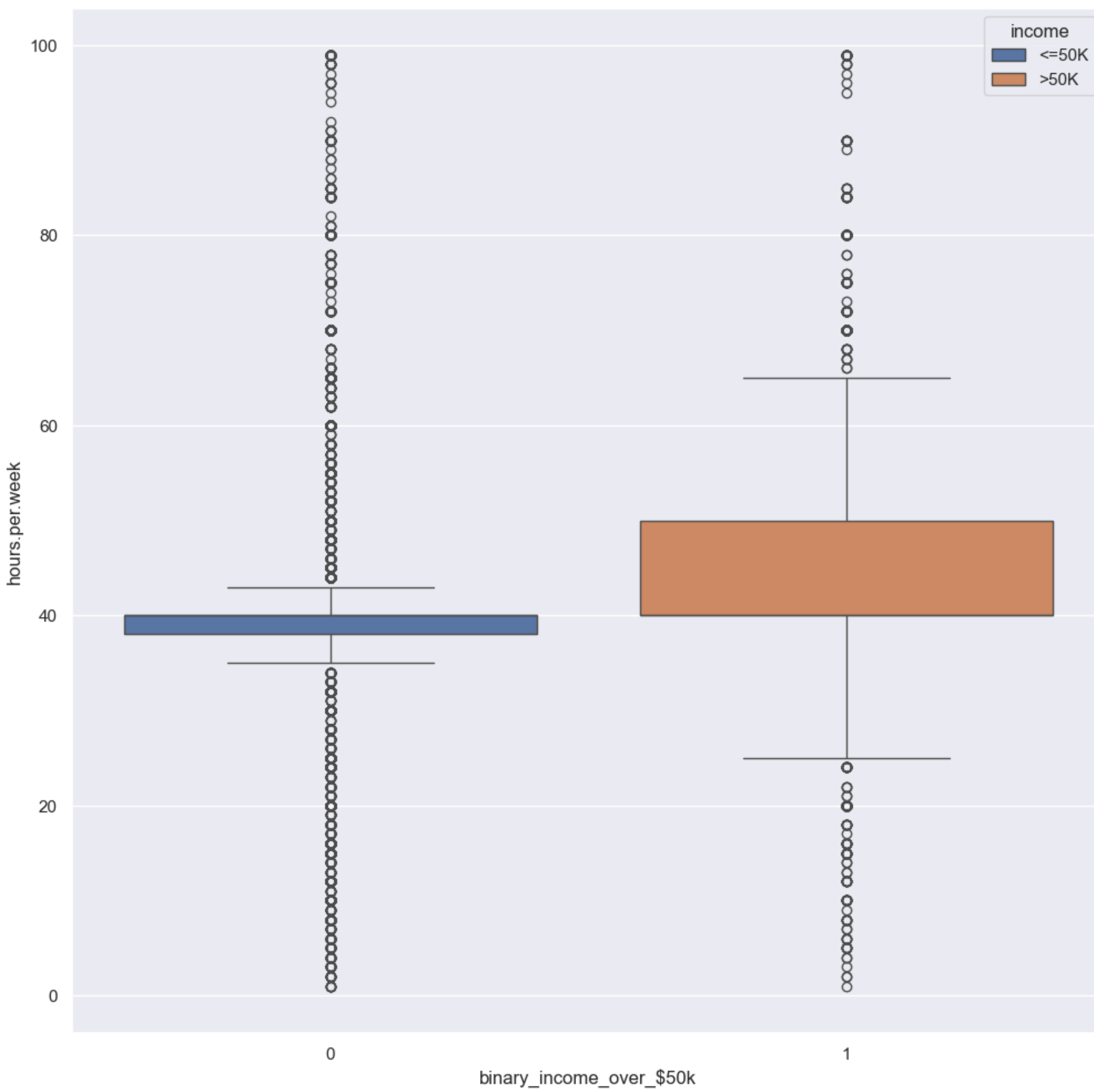
[16]:
```
print("Done By Brandon Cabrera")
def plot_boxplot(x:str, y:str) -> pd.DataFrame:
  """Plots a boxplot and returns a DataFrame containing descriptive stats shown␣
↪by the boxplot

  Args:
      x (String): A column name from adult_census_data
      y (String)): A column name from adult_census_data

  Returns:
      DataFrame: Contains descriptive stats of what's shown on the boxplot
  """
  fig = plt.figure(figsize=(12,12))
  fig = sns.boxplot(data = adult_census_data, x = adult_census_data[x], y =␣
↪adult_census_data[y], hue = adult_census_data['income'],)
  plt.show()
```

```
    group_0 = adult_census_data[adult_census_data['binary_income_over_$50k'] ==␣
↪0][y]
    group_1 = adult_census_data[adult_census_data['binary_income_over_$50k'] ==␣
↪1][y]
    group_combined = pd.DataFrame({'Income <= 50k(0)' : group_0.describe(),␣
↪'Income > 50k(1)': group_1.describe()})
    return group_combined
```

Done By Brandon Cabrera

[17]:
```
print("Done By Brandon Cabrera")
hours_per_week_info = plot_boxplot(x = 'binary_income_over_$50k', y = 'hours.
↪per.week')
hours_per_week_info
```

Done By Brandon Cabrera



[17]:

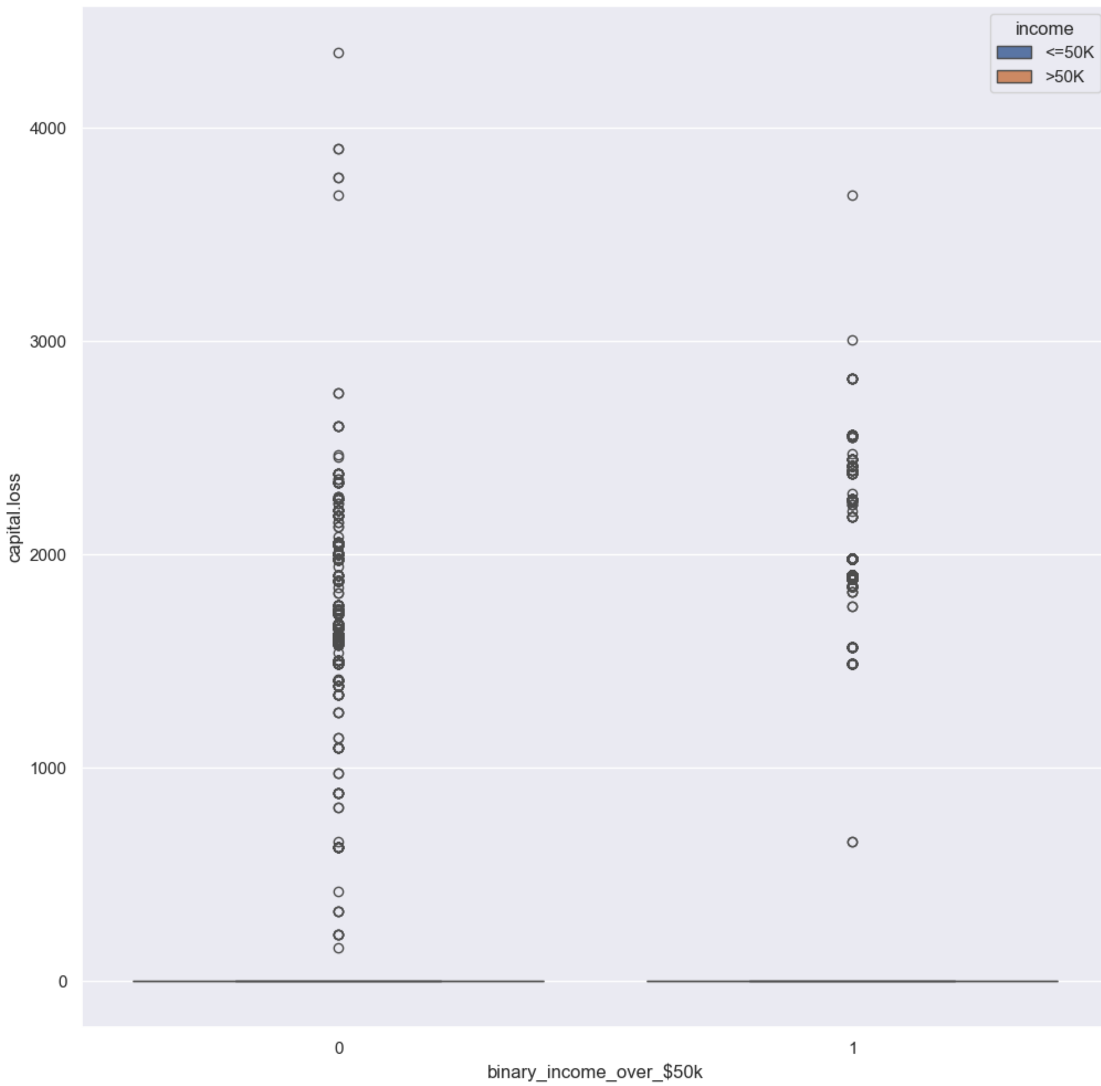
```
       Income <= 50k(0)  Income > 50k(1)
count      22654.000000      7508.000000
mean          39.348592        45.706580
std           11.950774        10.736987
min            1.000000         1.000000
25%           38.000000        40.000000
50%           40.000000        40.000000
75%           40.000000        50.000000
max           99.000000        99.000000
```

From the above boxplot, it's clear that people who made > 50k had a higher average number of hours worked per week, with 45.7 hours worked. Their standard deviation are similar, with a difference of around 1.22 hours worked. The quartiles for the two groups are close in value as well. This gives us enough information to answer the analysis question #1.

[18]:

```
print("Done By Brandon Cabrera")
capital_loss_info = plot_boxplot(x = 'binary_income_over_$50k', y = 'capital.
↪loss')
capital_loss_info
```

```
Done By Brandon Cabrera
```



[18]:

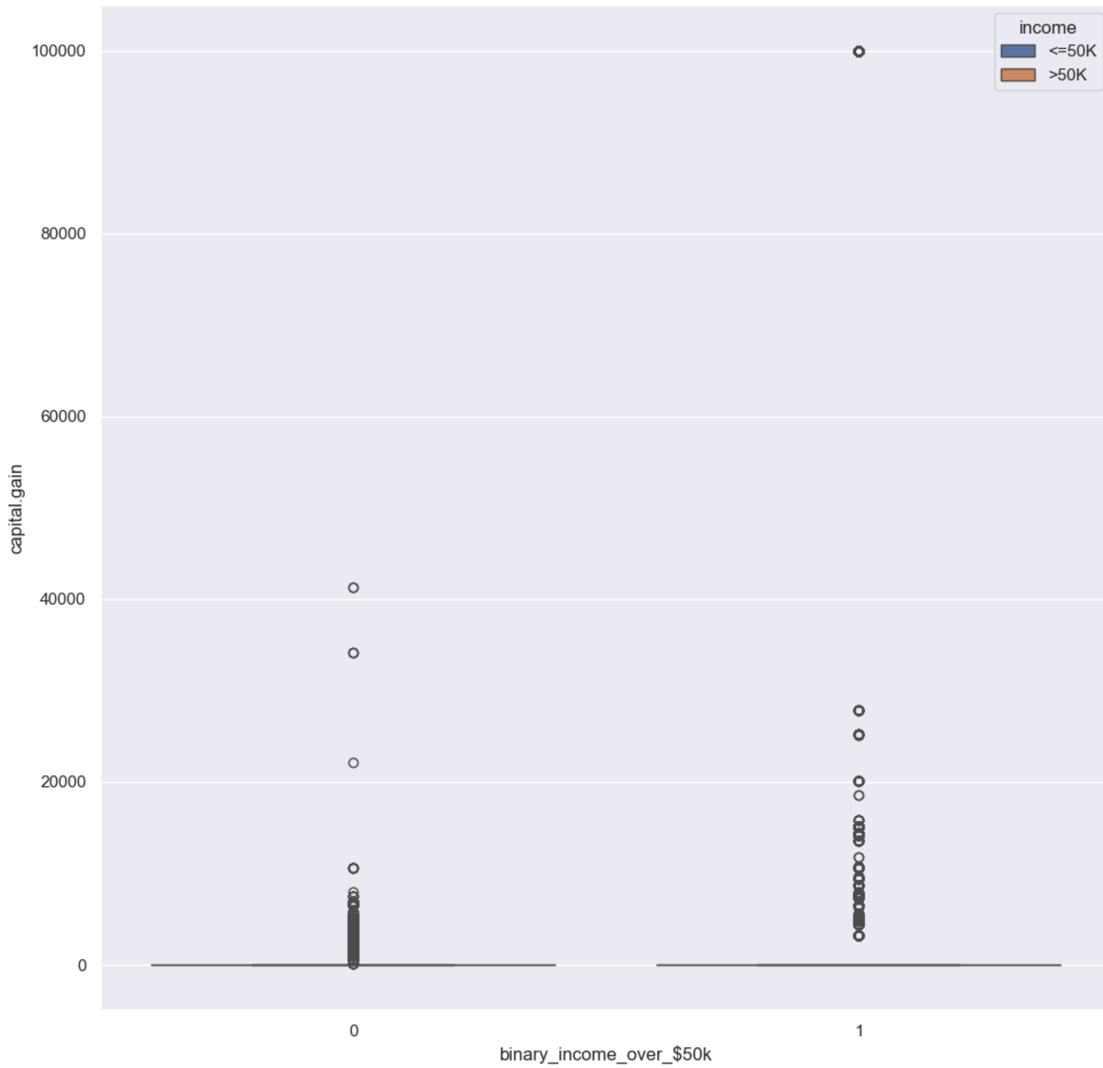
	Income <= 50k(0)	Income > 50k(1)
count	22654.000000	7508.000000
mean	53.448000	193.750666
std	310.270263	592.825590
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	4356.000000	3683.000000

The quartiles of the boxplot are hard to see since it's been squished to the bottom of the graph. From the descriptive stats, people who make over 50k have a mean of 193.75 capital loss, so they actually lose more from investments than people who make under 50k, with a mean of 53.44 capital loss. The max value for people who make <= 50k actually is higher than those who do make >

50k with values of 4356.0 and 3683.0, respectively.

[43]:
```
print("Done By Brandon Cabrera")
capital_gain_info = plot_boxplot(x = 'binary_income_over_$50k', y = 'capital.
 ↪gain')
capital_gain_info
```

```
Done By Brandon Cabrera
```



[43]:

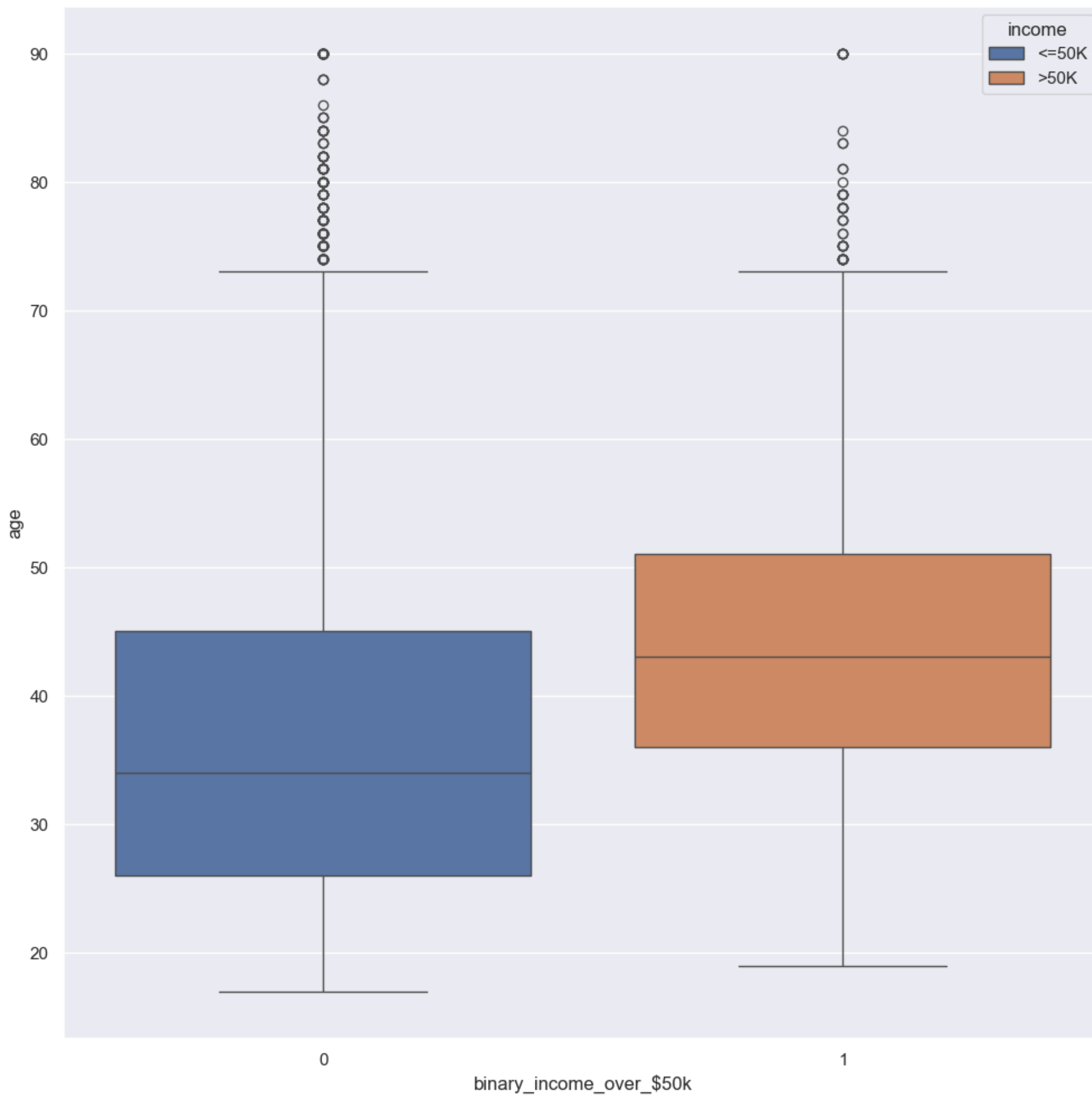
	Income <= 50k(0)	Income > 50k(1)
count	22654.000000	7508.000000
mean	148.893838	3937.679808
std	936.392280	14386.060019
min	0.000000	0.000000
25%	0.000000	0.000000

```
50%          0.000000        0.000000
75%          0.000000        0.000000
max      41310.000000    99999.000000
```

Once again, the quartiles for the boxplot have been squished to the bottom of the graph. The descriptive stats show that for the people who make > 50k, they have a mean of 3937.67 capital gain, while the people who make <= 50k have a mean of 148.89 capital gain. That is a sizeable difference between the two. The max value of capital gain is 41310.0 for people who make < 50k, and then for people who make > 50k it's 99999.0

[20]:
```
print("Done By Brandon Cabrera")
age_group_info = plot_boxplot(x = 'binary_income_over_$50k', y='age')
age_group_info
```

```
Done By Brandon Cabrera
```



[20]:

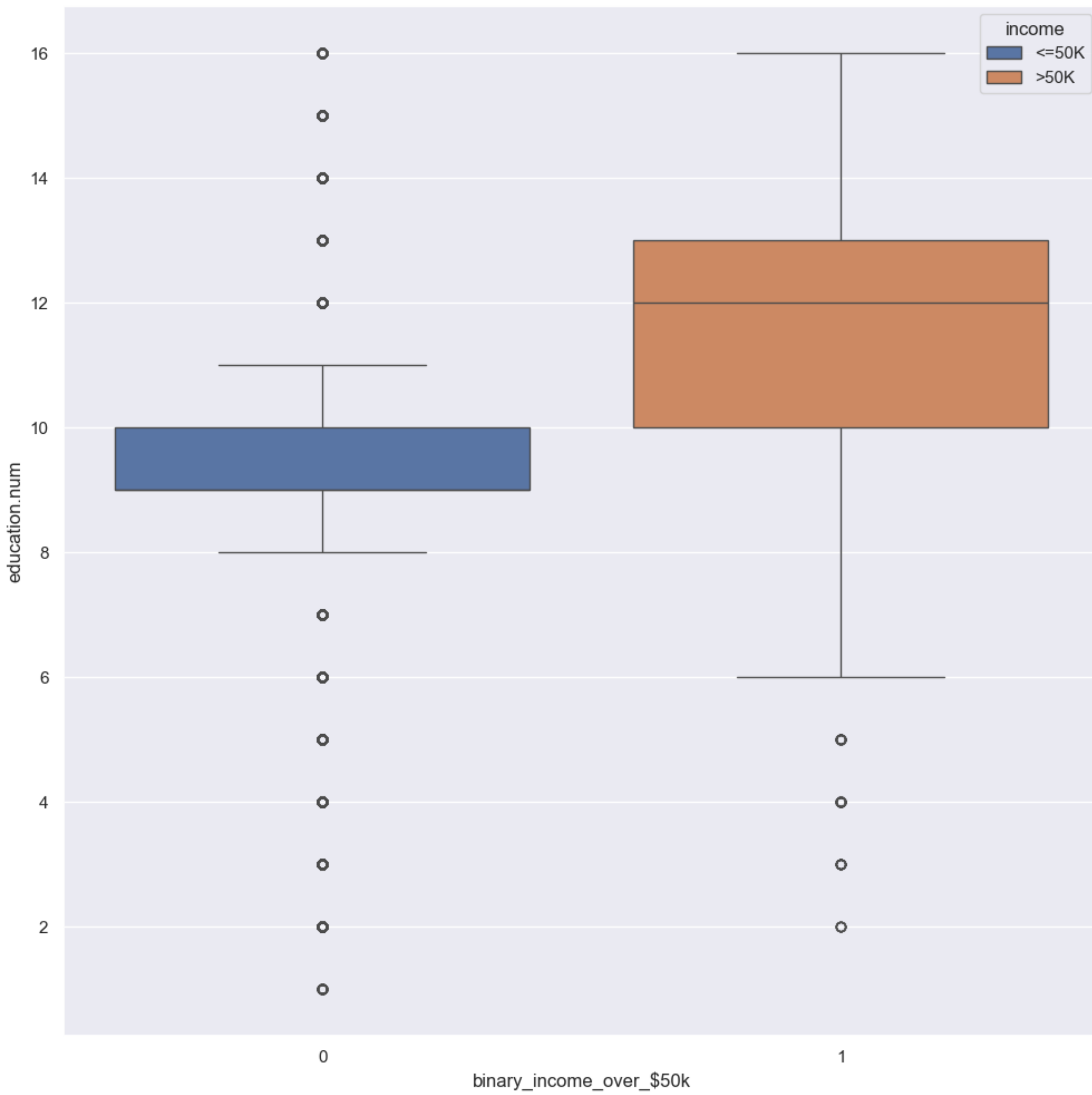
```
       Income <= 50k(0)  Income > 50k(1)
count      22654.000000      7508.000000
mean          36.608060        43.959110
std           13.464631        10.269633
min           17.000000        19.000000
25%           26.000000        36.000000
50%           34.000000        43.000000
75%           45.000000        51.000000
max           90.000000        90.000000
```

From the above figure and the statistics, the mean age of people who make > 50k is higher than the mean age of people who make <= 50k. With values of 43.95 years old and 36.60 years old, respectively.

[21]:

```
print("Done By Brandon Cabrera")
education_num_info = plot_boxplot(x = 'binary_income_over_$50k', y = 'education.
↪num')
education_num_info
```

```
Done By Brandon Cabrera
```



[21]:

	Income <= 50k(0)	Income > 50k(1)
count	22654.000000	7508.000000
mean	9.629116	11.606420
std	2.413596	2.368423
min	1.000000	2.000000
25%	9.000000	10.000000
50%	9.000000	12.000000
75%	10.000000	13.000000
max	16.000000	16.000000

The above information tells us that the average education number for people who make > 50k is 12, if we round up to the nearest number, which is equivalent to Assoc-acdm in terms of education level. Then, for the people who make <= 50k, rounding up to the nearest whole number, the average education number is 10, meaning they have some-college. This answers analysis question

#3, the average education level for both groups is now known.

7.1.1 Numerical Columns Correlations

Next let's see how correlated the numerical columns are to each binary column.

[22]:
```
print("Done By Brandon Cabrera")
adult_census_data.corr(numeric_only= True)[['binary_income_over_$50k',␣
↪'binary_income_equal_under_$50k']]
```

```
Done By Brandon Cabrera
```

[22]:
```
                               binary_income_over_$50k  \
age                                           0.241998
education.num                                 0.335286
capital.gain                                  0.221196
capital.loss                                  0.150053
hours.per.week                                0.229480
binary_income_over_$50k                       1.000000
binary_income_equal_under_$50k               -1.000000

                               binary_income_equal_under_$50k
age                                                 -0.241998
education.num                                       -0.335286
capital.gain                                        -0.221196
capital.loss                                        -0.150053
hours.per.week                                      -0.229480
binary_income_over_$50k                             -1.000000
binary_income_equal_under_$50k                       1.000000
```

From the correlation matrix analysis, question #4 and analysis question #6 can be answered. The correlation between capital gain and a person making over > 50k is 0.221, indicating a weak positive relationship. This makes sense since not everyone who is making money from investments might be making a profit compared to their losses, or the money made isn't much. The column with the highest amount of correlation, in terms of magnitude, for both binary columns is education.num with a value of 0.335. This is a weak relationship, indicating that as a person's education level becomes higher, they are more likely to make >50k. If we look at it from the perspective of making <= 50k, then it indicates that as a person's education level becomes higher than they are less likely to make <= 50k. Capital loss has the least amount of correlation with both of the income groups.

7.2 Exploring qualtative columns

For visualizing the qualtative colums let's use bar chart to help answer the analysis questions. Let's get a list of the qualtative columns.

[23]:
```
print("Done by Brandon Cabrera")
adult_census_data.select_dtypes(include = 'object').columns
```

```
Done by Brandon Cabrera
```

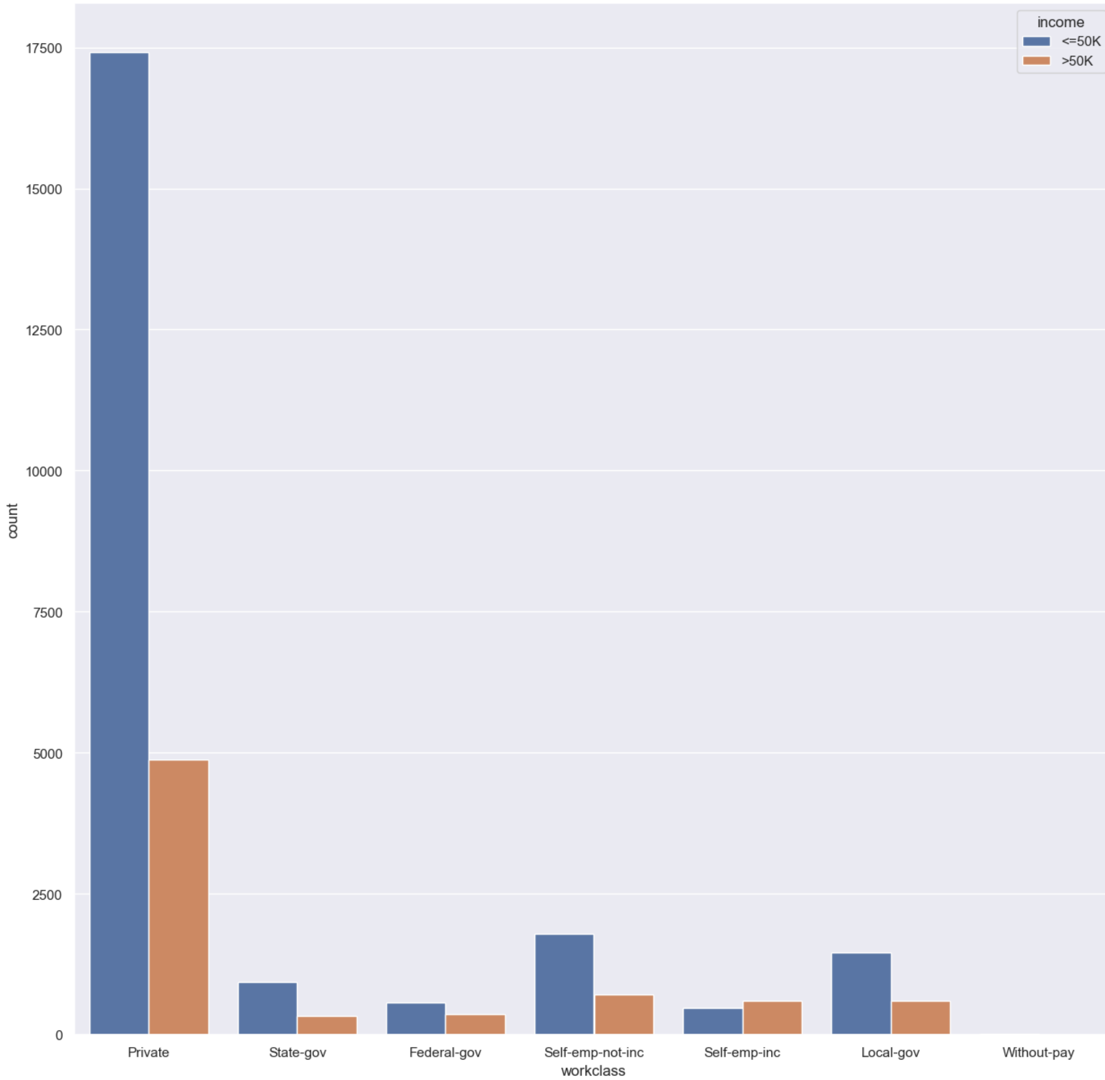
[23]:
```
Index(['workclass', 'education', 'marital.status', 'occupation',
       'relationship', 'race', 'sex', 'native.country', 'income'],
      dtype='object')
```

[24]:
```
print("Done by Brandon Cabrera")
def plot_countplot(col: str, figsize = (15,15)) -> pd.DataFrame:
    """Creates a countplot and returns a frequency table that represents the␣
 ↪countplot

    Args:
        col (str): A column name from adult_census_data

    Returns:
        pd.DataFrame: A Frequency table that represents the countplot that is made
    """
    fig = plt.figure(figsize = figsize)
    fig = sns.countplot(x=adult_census_data[col], hue =␣
 ↪adult_census_data['income'])
    plt.show()
    return pd.crosstab(index= adult_census_data[col], columns =␣
 ↪adult_census_data['binary_income_over_$50k']) #creates a frequency table
```

```
Done by Brandon Cabrera
```

[25]:
```
print("Done by Brandon Cabrera")
workclass_countplot_table = plot_countplot('workclass')
workclass_countplot_table.sort_values(by=0, ascending = False) # sort by column␣
 ↪0 and go from largest to smallest
```

```
Done by Brandon Cabrera
```

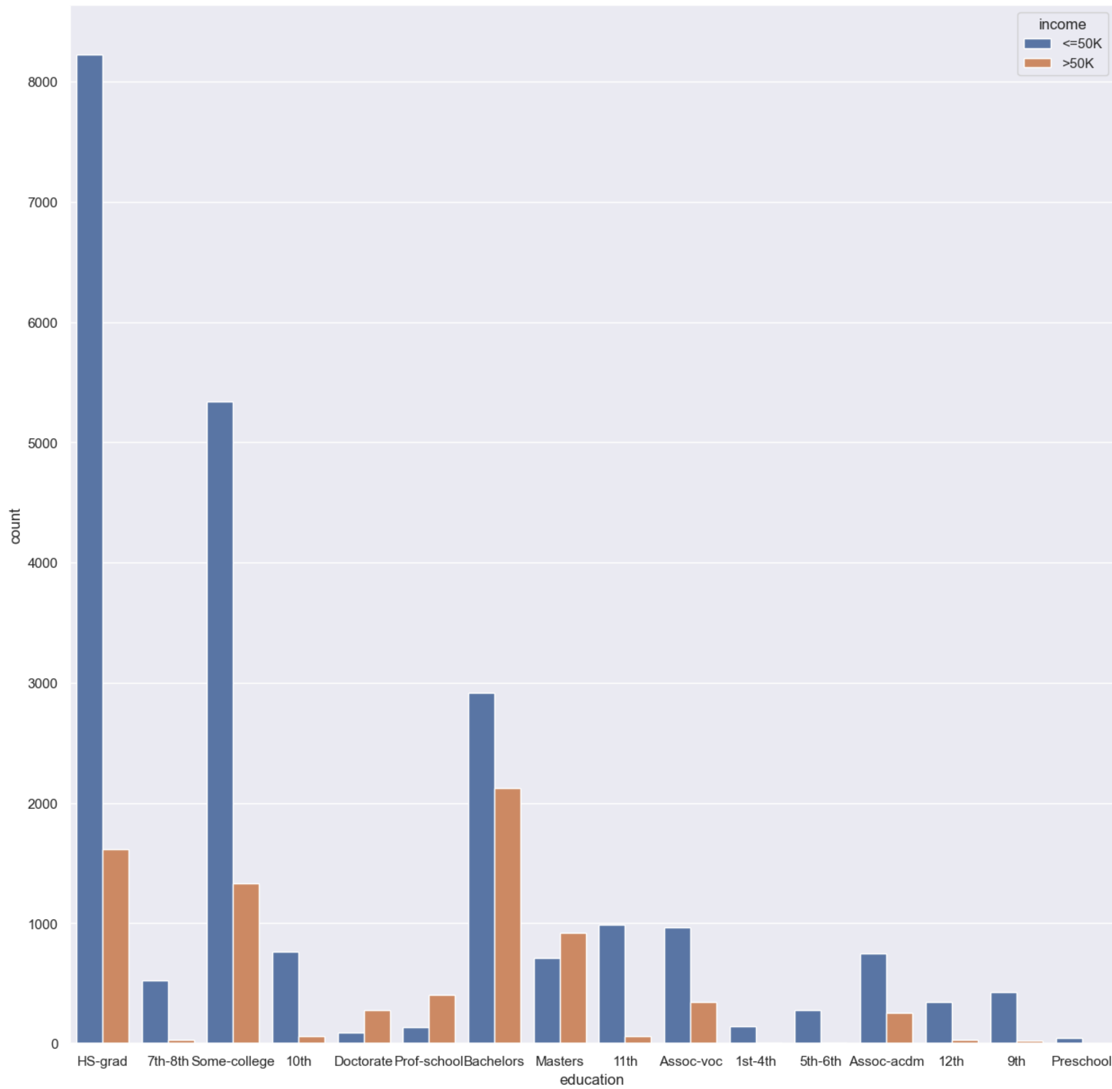


[25]:
```
binary_income_over_$50k      0     1
workclass
Private                  17410  4876
Self-emp-not-inc          1785   714
Local-gov                 1458   609
State-gov                  935   344
Federal-gov                578   365
Self-emp-inc               474   600
Without-pay                 14     0
```

The above figure shows that the private workclass has the most amount of people making $>$ 50k, as well as the most amount of people making less $<=$ 50k. There are 4876 people who make $>$ \$50k and who are a part of the private workclass. This answers analysis question #7. A trend for the data is that the $<=$ 50k income group has more people in it than the $>$ 50k income group for every workclass, except for the self-emp-inc workclass.

[26]:
```
print("Done by Brandon Cabrera")
education_countplot_table = plot_countplot('education')
education_countplot_table.sort_values(by=0, ascending = False) # sort by column
 ↪0 and go from largest to smallest
```

Done by Brandon Cabrera



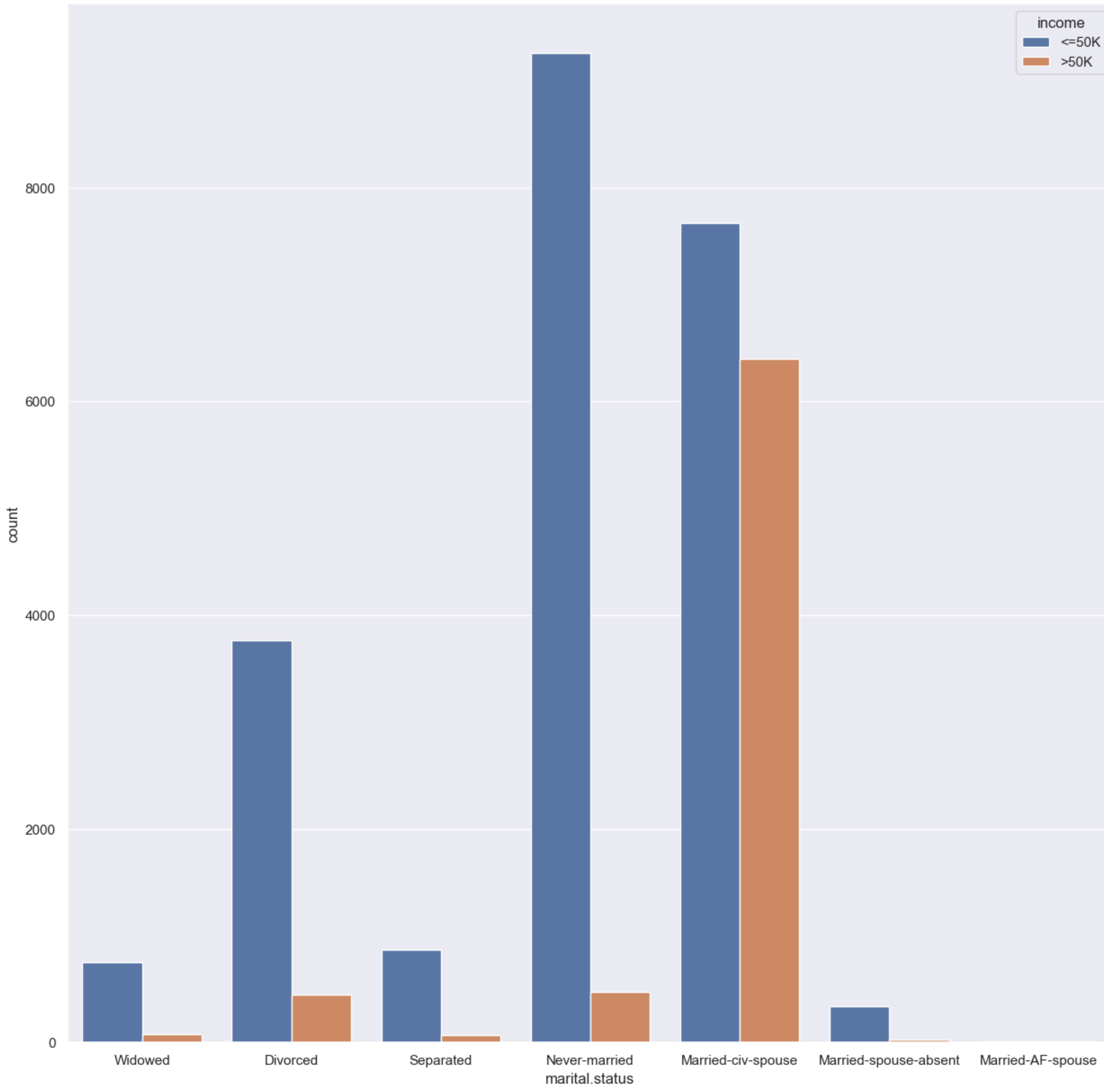
[26]:
```
binary_income_over_$50k     0     1
education
HS-grad                  8223  1617
Some-college             5342  1336
Bachelors                2918  2126
```

```
11th                          989    59
Assoc-voc                     963   344
10th                          761    59
Assoc-acdm                    752   256
Masters                       709   918
7th-8th                       522    35
9th                           430    25
12th                          348    29
5th-6th                       276    12
1st-4th                       145     6
Prof-school                   136   406
Doctorate                      95   280
Preschool                      45     0
```

It's clear that education level with the most amount of people who are making <= 50k is the HS-grad education level, from the above figure. We can also see that for post-graduate education levels, there is more people who make over >50k than there are people who make <= 50k. We can see the opposite effect for people whose highest education level is a Bachelor's degree or lower.

[27]:
```
print("Done by Brandon Cabrera")
marital_status_countplot_table = plot_countplot('marital.status')
marital_status_countplot_table.sort_values(by=0, ascending = False) # sort by␣
↪column 0 and go from largest to smallest
```

```
Done by Brandon Cabrera
```

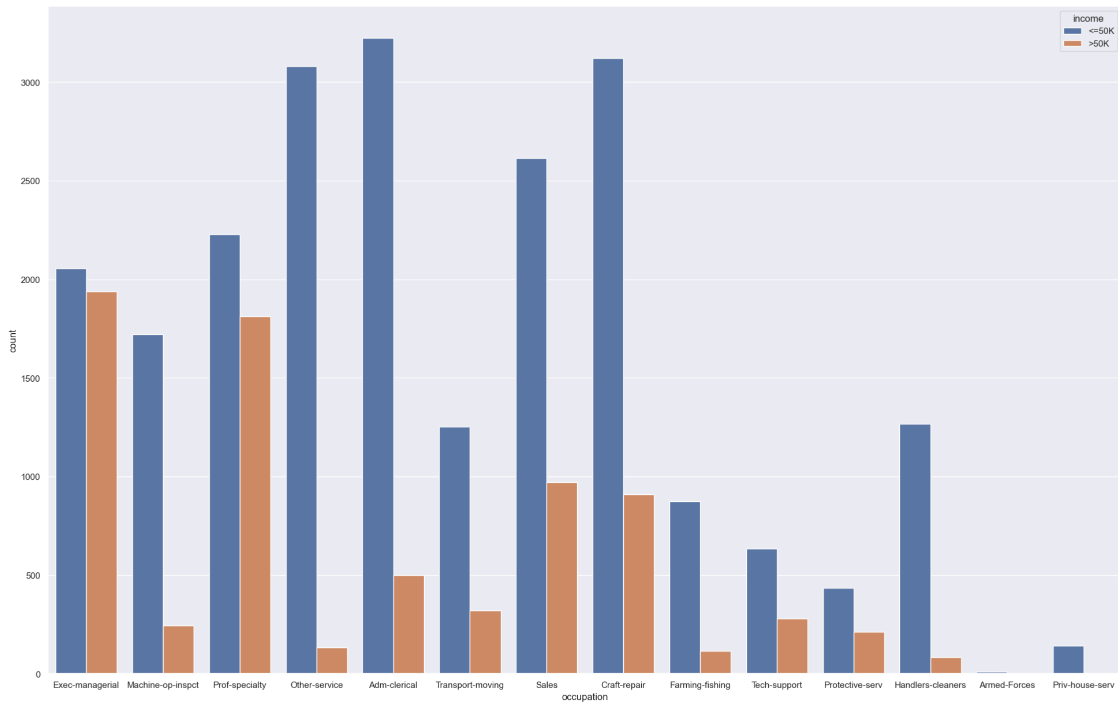


[27]:
```
binary_income_over_$50k     0     1
marital.status
Never-married            9256   470
Married-civ-spouse       7666  6399
Divorced                 3762   452
Separated                 873    66
Widowed                   747    80
Married-spouse-absent     339    31
Married-AF-spouse          11    10
```

From the above figure, analysis question #5 can be answered. The marital status with the most amount of people making > 50k is married-civ-spouse. The marital status with the most amount of people making $<= 50$k is Never-married.

[28]:
```python
print("Done by Brandon Cabrera")
occupation_countplot_table = plot_countplot('occupation', figsize= (24,15))
occupation_countplot_table.sort_values(by=0, ascending = False) # sort by column 0 and go from largest to smallest
```

Done by Brandon Cabrera



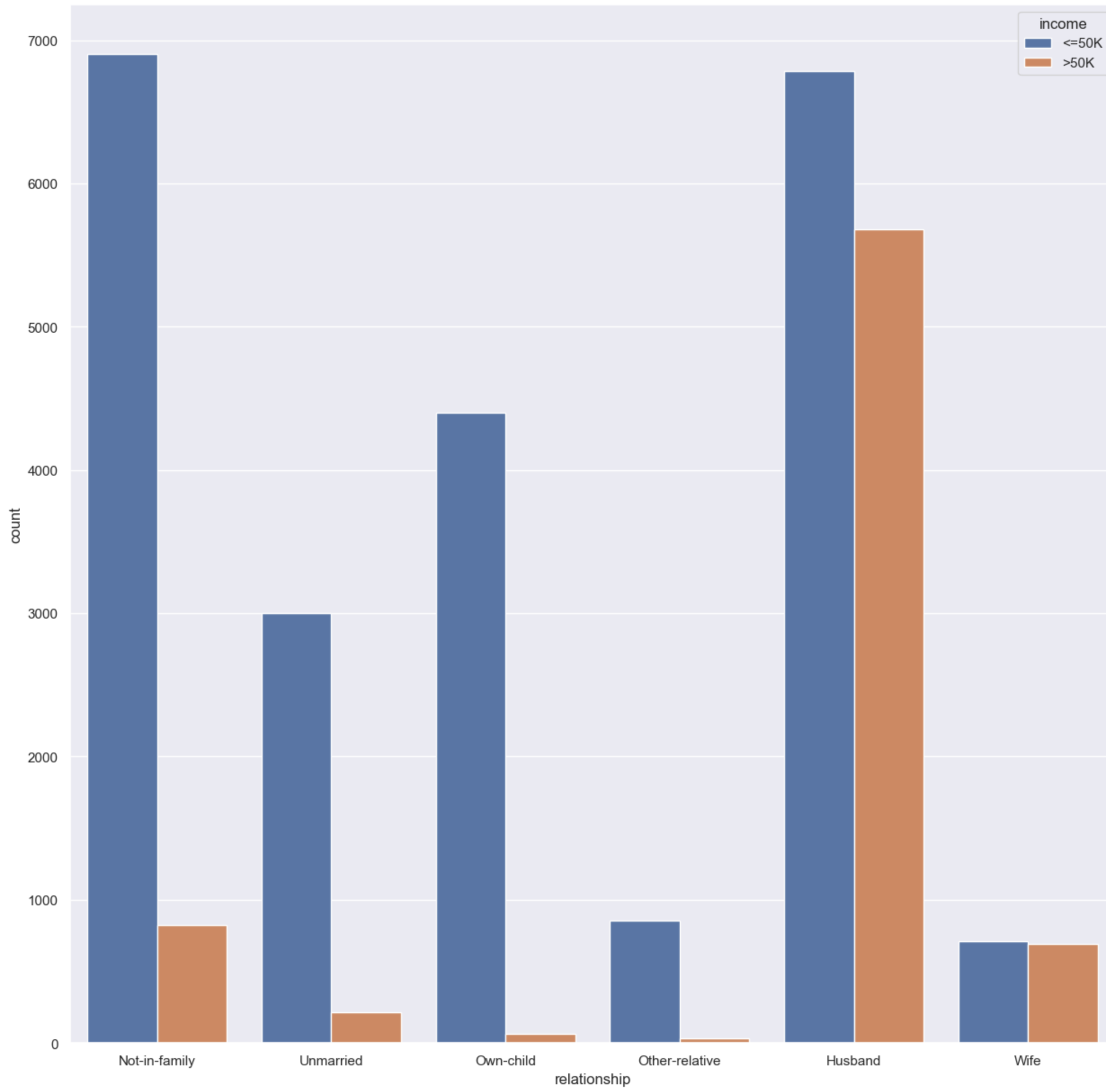
[28]:

binary_income_over_$50k	0	1
occupation		
Adm-clerical	3223	498
Craft-repair	3122	908
Other-service	3080	132
Sales	2614	970
Prof-specialty	2227	1811
Exec-managerial	2055	1937
Machine-op-inspct	1721	245
Handlers-cleaners	1267	83
Transport-moving	1253	319
Farming-fishing	874	115
Tech-support	634	278
Protective-serv	434	210
Priv-house-serv	142	1
Armed-Forces	8	1

From the above figure, it's evident that most of the occupations have a considerable amount of more people making <= 50k than people making >= 50k. Except for the occupations, Prof-specialty and Exec-managerial, where the difference is a lot smaller.

[29]:
```
print("Done by Brandon Cabrera")
relationship_countplot_table = plot_countplot(col = 'relationship')
relationship_countplot_table.sort_values(by=0, ascending = False) # sort by␣
 ↪column 0 and go from largest to smallest
```

Done by Brandon Cabrera



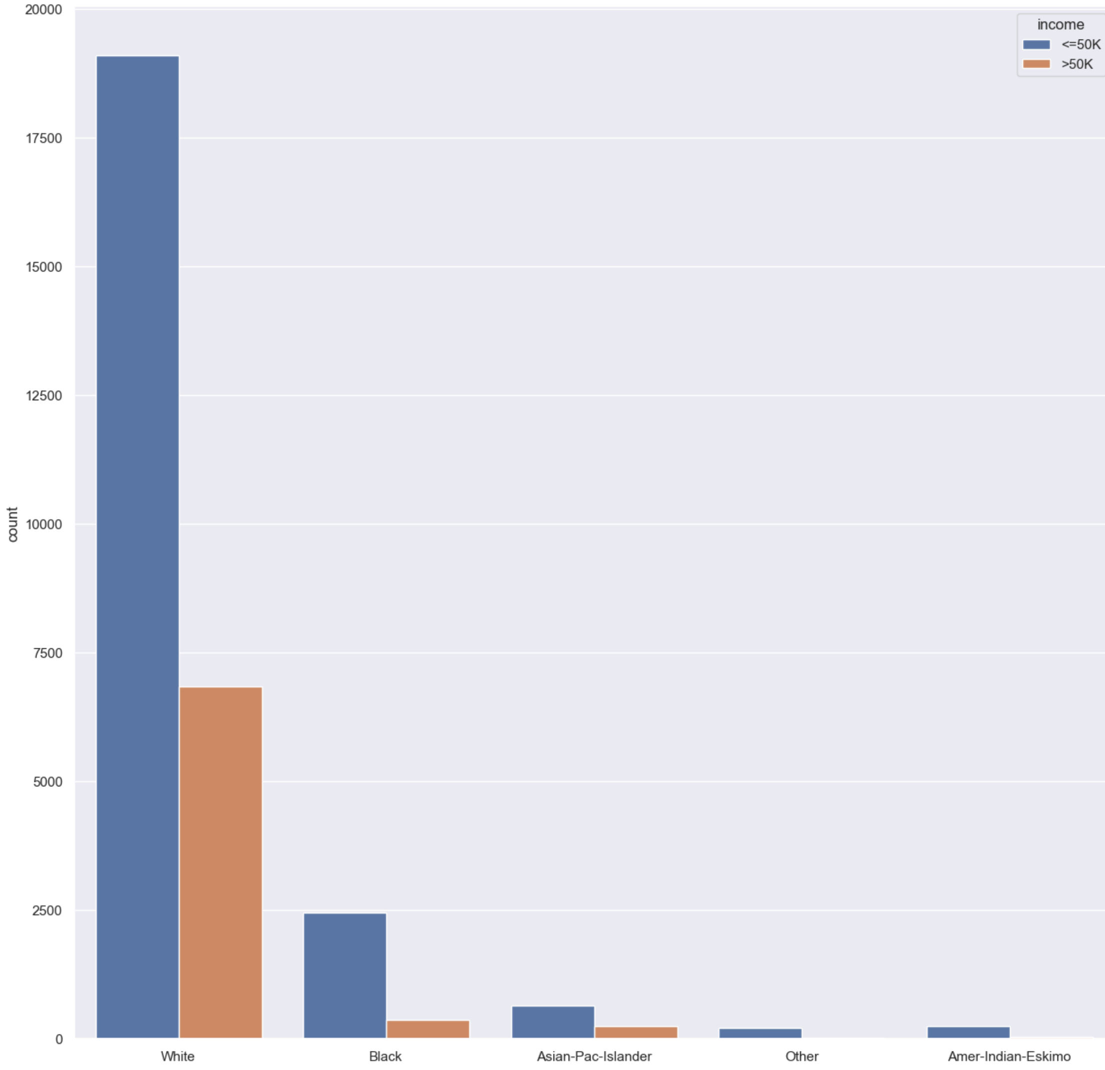
[29]:
```
binary_income_over_$50k     0     1
relationship
Not-in-family            6903   823
Husband                  6784  5679
```

```
Own-child                4402    64
Unmarried                2999   213
Other-relative            854    35
Wife                      712   694
```

The relationship columns represent the individual's relationship inside the household, so it makes sense that the husband and wife relationship is the one with the most amount of people making > 50k as opposed to the other relationship statuses.

[30]:
```
print("Done by Brandon Cabrera")
race_countplot_table = plot_countplot(col = 'race')
race_countplot_table.sort_values(by=0, ascending = False) # sort by column 0␣
 ↪and go from largest to smallest
```

```
Done by Brandon Cabrera
```

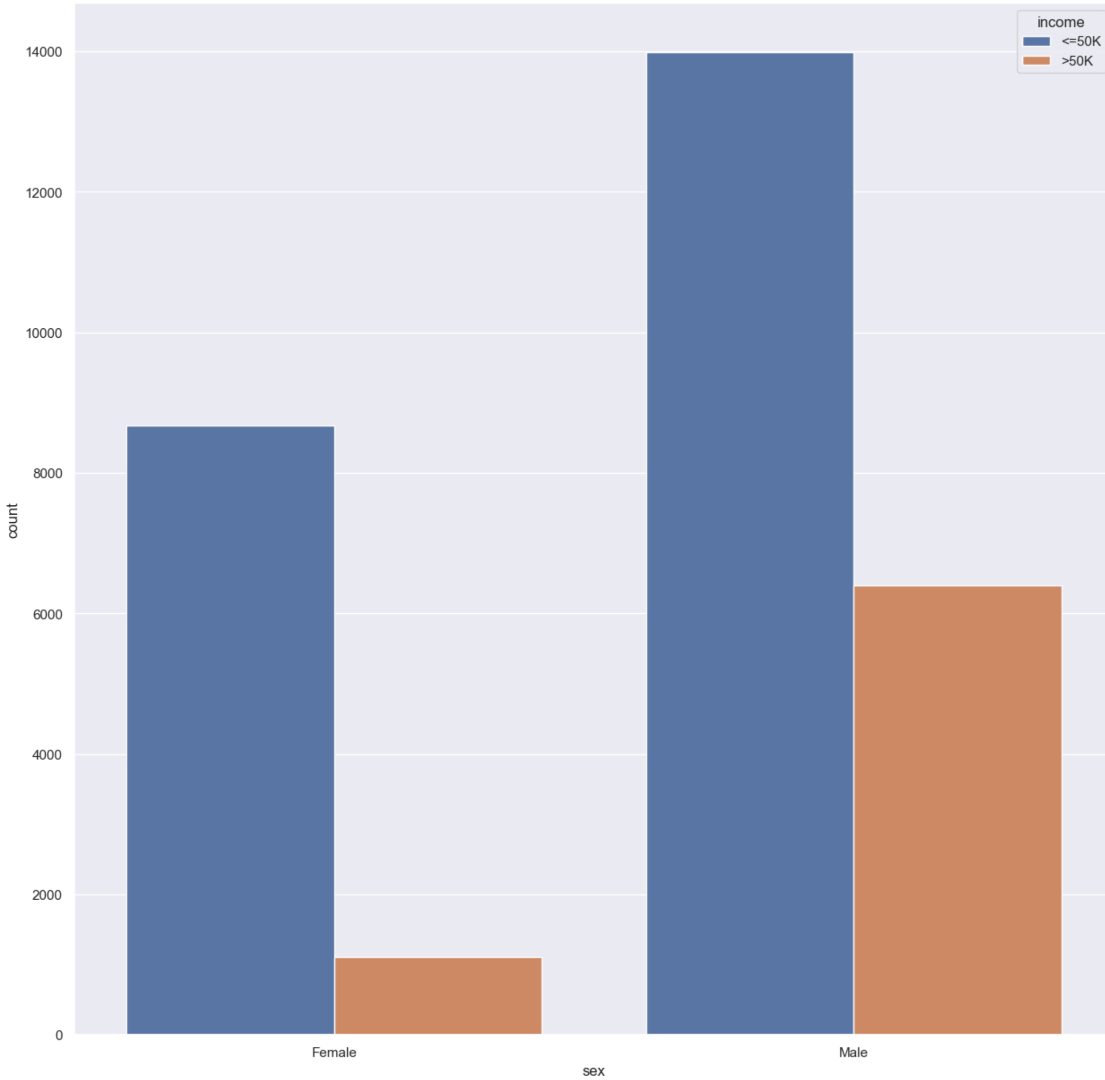


[30]:
```
binary_income_over_$50k      0     1
race
White                    19094  6839
Black                     2451   366
Asian-Pac-Islander         647   248
Amer-Indian-Eskimo         252    34
Other                      210    21
```

Analysis question #10 can now be answered. It is clear the race with the most amount of people making > 50k is the white race and it's also the race with the most amount of people making <= 50k. It's worth noting that I am considering only the frequency and not the percentages, which would be a fairer assessment of which race tends to make more.

[31]:
```python
print("Done by Brandon Cabrera")
sex_countplot_table = plot_countplot(col='sex')
sex_countplot_table.sort_values(by=0, ascending = False) # sort by column 0 and␣
 ↪go from largest to smallest
```

```
Done by Brandon Cabrera
```

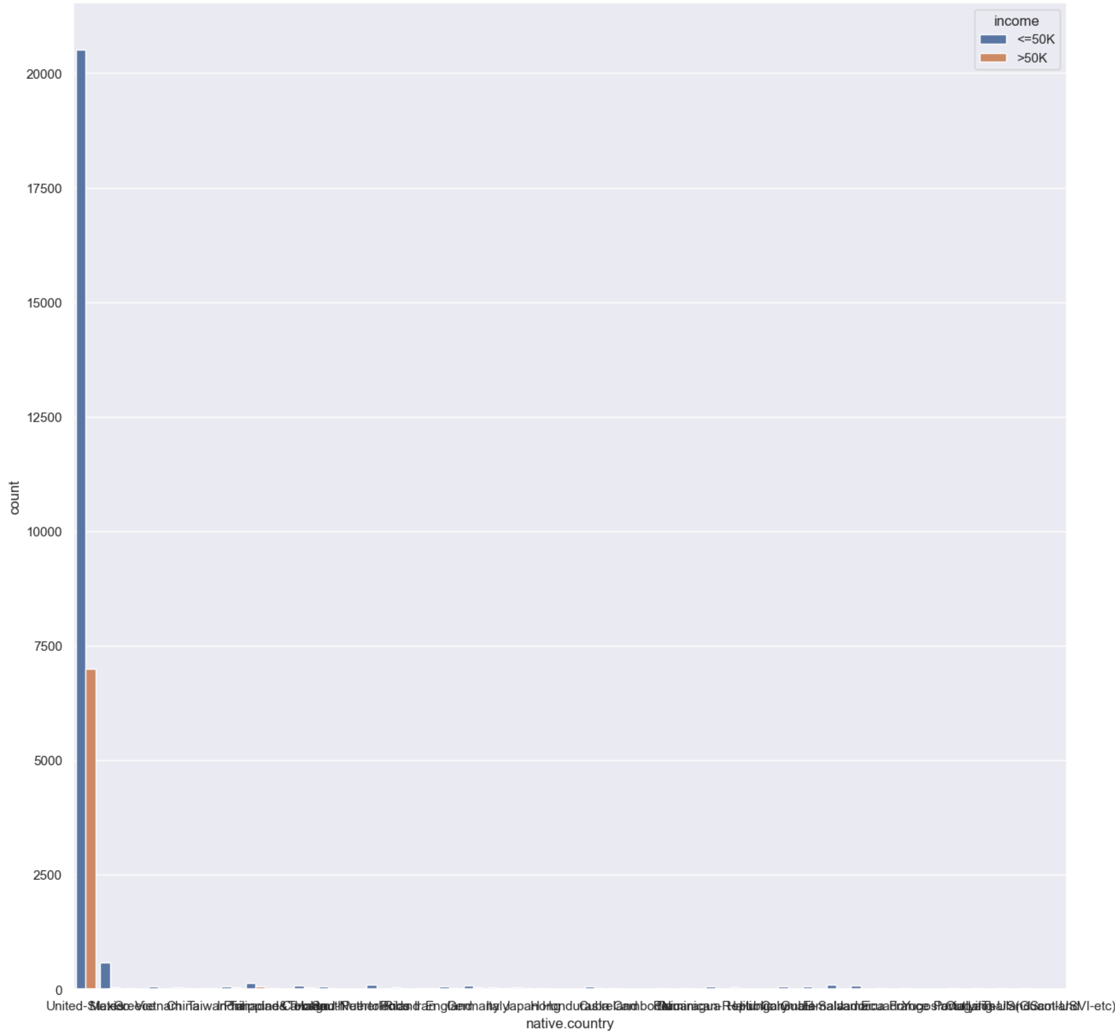


[31]:
```
binary_income_over_$50k      0     1
sex
Male                     13984  6396
Female                    8670  1112
```

The above information shows that the sex with the most amount of people who make > 50k and the most of people who make <= 50k is the male sex. This answers analysis question #8. In both groups, there is a considerable amount more people making <= 50k.

[32]:
```
print("Done by Brandon Cabrera")
native_country_countplot_table = plot_countplot(col = 'native.country')
native_country_countplot_table.sort_values(by=0, ascending = False) # sort by␣
↪column 0 and go from largest to smallest
```

```
Done by Brandon Cabrera
```



[32]:
```
binary_income_over_$50k        0     1
native.country
United-States              20509  6995
Mexico                       577    33
Philippines                  128    60
Puerto-Rico                   97    12
El-Salvador                   91     9
Germany                       84    44
Canada                        71    36
Jamaica                       70    10
Cuba                          67    25
Dominican-Republic            65     2
Guatemala                     60     3
India                         60    40
Vietnam                       59     5
```

South	57	14
England	56	30
Columbia	54	2
China	48	20
Poland	45	11
Italy	44	24
Haiti	38	4
Japan	36	23
Nicaragua	31	2
Portugal	30	4
Peru	28	2
Iran	24	18
Taiwan	23	19
Ecuador	23	4
Greece	21	8
Ireland	19	5
Trinadad&Tobago	16	2
Laos	15	2
France	15	12
Outlying-US(Guam-USVI-etc)	14	0
Thailand	14	3
Hong	13	6
Cambodia	11	7
Honduras	11	1
Hungary	10	3
Yugoslavia	10	6
Scotland	9	2
Holand-Netherlands	1	0

There are too many countries in the dataset to properly show on the countplot, but the frequency table shows that the United States has the most amount of people in both income categories. Mexico has the second most amount of people making <= 50k, followed by the Philippines.

7.2.1 Pivot Tables for Qualtative Columns

Now I am going to make some pivot tables for the qualtative columns and for each qualtative column we will seperate them into the two income groups and have them summarize the numeric columns by calculating the mean of each numeric column. Although I am going to make one for each qualtative column I'm most intersted into the ones that help answer the remaining analysis questisions, #3 and #9.

[33]:
```
print("Done by Brandon Cabrera")
workclass_pivot_table = pd.pivot_table(data= adult_census_data, index =␣
↪['workclass', 'income'], values= ['age', 'education.num', 'capital.gain',␣
↪'capital.loss', 'hours.per.week'])
workclass_pivot_table
```

```
Done by Brandon Cabrera
```

[33]:

```
                                 age  capital.gain  capital.loss  education.num  \
workclass        income
Federal-gov      <=50K  40.605536    176.503460     93.015571      10.468858
                 >50K   45.701370   1870.849315    141.369863      11.706849
Local-gov        <=50K  40.714678    166.970508     80.163237      10.569959
                 >50K   44.205255   2414.738916    182.528736      12.154351
Private          <=50K  35.106720    138.144170     49.671051       9.438369
                 >50K   42.820139   3528.184988    186.597621      11.416120
Self-emp-inc     <=50K  43.130802    182.476793     56.662447      10.251055
                 >50K   48.316667   8467.080000    230.010000      11.891667
Self-emp-not-inc <=50K  44.451541    223.535014     61.985434       9.680112
                 >50K   46.411765   6137.133053    249.539216      11.539216
State-gov        <=50K  37.240642    139.203209     40.529412      10.790374
                 >50K   45.127907   2165.909884    191.549419      12.869186
Without-pay      <=50K  47.785714    487.857143      0.000000       9.071429

                        hours.per.week
workclass        income
Federal-gov      <=50K       39.982699
                 >50K        43.334247
Local-gov        <=50K       39.748971
                 >50K        44.003284
Private          <=50K       38.782596
                 >50K        45.493437
Self-emp-inc     <=50K       46.966245
                 >50K        50.253333
Self-emp-not-inc <=50K       43.507003
                 >50K        46.745098
State-gov        <=50K       37.170053
                 >50K        44.174419
Without-pay      <=50K       32.714286
```

Through the above pivot table, there is a trend that the average age for the > 50k group for every workclass is higher than the average age for the $<= 50$k group of the same workclass. We can also see this same trend with all the other numeric columns; people in the > 50k group have more capital gain, capital loss, higher education levels, and more hours worked per week than their counterparts in the $<= 50$k group.

[34]:

```
print("Done by Brandon Cabrera")
education_pivot_table = pd.pivot_table(data= adult_census_data, index =
 ↪['education', 'income'], values= ['age', 'education.num', 'capital.gain',
 ↪'capital.loss', 'hours.per.week'])
education_pivot_table
```

```
Done by Brandon Cabrera
```

[34]:

```
                        age  capital.gain  capital.loss  education.num  \
education    income
```

10th	<=50K	36.980289	97.618922	42.540079	6.0
	>50K	49.728814	4243.423729	316.728814	6.0
11th	<=50K	31.731041	80.803842	43.089990	7.0
	>50K	42.966102	2503.406780	210.915254	7.0
12th	<=50K	30.899425	89.183908	30.321839	8.0
	>50K	45.379310	2381.310345	63.724138	8.0
1st-4th	<=50K	44.317241	65.634483	55.993103	2.0
	>50K	52.000000	1281.333333	0.000000	2.0
5th-6th	<=50K	41.554348	105.786232	67.797101	3.0
	>50K	43.833333	1647.833333	157.250000	3.0
7th-8th	<=50K	47.260536	185.296935	67.026820	4.0
	>50K	53.171429	1130.714286	54.342857	4.0
9th	<=50K	39.793023	130.300000	21.179070	5.0
	>50K	49.080000	4207.080000	163.160000	5.0
Assoc-acdm	<=50K	35.902926	114.837766	65.966755	12.0
	>50K	41.351562	1847.667969	177.835938	12.0
Assoc-voc	<=50K	36.741433	194.452752	46.686397	11.0
	>50K	42.459302	2257.125000	136.020349	11.0
Bachelors	<=50K	35.893763	165.098355	59.048321	13.0
	>50K	42.412982	3889.806209	198.828786	13.0
Doctorate	<=50K	44.357895	248.336842	51.884211	16.0
	>50K	48.071429	6654.185714	337.610714	16.0
HS-grad	<=50K	37.451417	153.723945	53.116502	9.0
	>50K	44.690167	2804.876314	160.666048	9.0
Masters	<=50K	41.895628	293.393512	83.358251	14.0
	>50K	45.164488	4300.569717	240.202614	14.0
Preschool	<=50K	41.288889	1018.177778	75.355556	1.0
Prof-school	<=50K	42.882353	156.375000	95.808824	15.0
	>50K	44.706897	14274.081281	280.923645	15.0
Some-college	<=50K	34.196181	126.955447	50.589105	10.0
	>50K	43.889222	2442.908683	157.123503	10.0

		hours.per.week
education	income	
10th	<=50K	36.988173
	>50K	43.610169
11th	<=50K	33.555106
	>50K	44.898305
12th	<=50K	34.939655
	>50K	44.793103
1st-4th	<=50K	37.944828
	>50K	48.833333
5th-6th	<=50K	38.521739
	>50K	45.166667
7th-8th	<=50K	39.609195
	>50K	47.914286
9th	<=50K	38.413953

```
             >50K          44.840000
Assoc-acdm   <=50K         39.953457
             >50K          44.800781
Assoc-voc    <=50K         41.298027
             >50K          43.790698
Bachelors    <=50K         40.920493
             >50K          45.731891
Doctorate    <=50K         46.694737
             >50K          48.217857
HS-grad      <=50K         40.222303
             >50K          45.210884
Masters      <=50K         41.703808
             >50K          46.200436
Preschool    <=50K         36.866667
Prof-school  <=50K         43.816176
             >50K          49.352217
Some-college <=50K         37.999064
             >50K          45.056886
```

The above pivot table helps to answer the analysis question #2. For a person whose highest education level is HS-grad, the average age for people of that education level who make > 50k is 45 years old, if we round up to the nearest whole number. Another pattern in this pivot table is that for the higher education levels past Some-college, the difference in the average age between the income groups is a lot smaller. The Doctorate level has a mean age of 44 years old for the $<= 50$k group and a mean age of 48 years old for the > 50k group. The Some-college group has a mean age of 34 years old for it's $<= 50$k group and a mean age of 44 years old for it's > 50k group

[35]:
```
print("Done by Brandon Cabrera")
marital_status_pivot_table = pd.pivot_table(data= adult_census_data, index =␣
 ↪['marital.status', 'income'], values= ['age', 'education.num', 'capital.
 ↪gain', 'capital.loss', 'hours.per.week'])
marital_status_pivot_table
```

```
Done by Brandon Cabrera
```

[35]:
```
                                    age  capital.gain  capital.loss  \
marital.status        income
Divorced              <=50K   42.566986    142.161350     57.413610
                      >50K    45.435841   5838.396018    141.207965
Married-AF-spouse     <=50K   30.090909      0.000000      0.000000
                      >50K    31.300000    729.800000      0.000000
Married-civ-spouse    <=50K   41.636968    219.403861     61.375815
                      >50K    44.127989   3605.772152    198.067042
Married-spouse-absent <=50K   39.631268    113.784661     42.628319
                      >50K    47.645161   6600.580645    130.193548
Never-married         <=50K   27.974395     98.092589     45.740169
                      >50K    38.053191   6011.123404    179.006383
Separated             <=50K   39.174112    117.262314     48.349370
```

```
                     >50K   42.348485  6614.727273   232.621212
Widowed              <=50K  57.693440   143.764391    59.281124
                     >50K   58.287500  4726.162500   248.762500

                            education.num  hours.per.week
marital.status        income
Divorced              <=50K      9.852472       40.808612
                      >50K      11.918142       47.460177
Married-AF-spouse     <=50K      9.363636       45.727273
                      >50K      11.000000       42.600000
Married-civ-spouse    <=50K      9.360031       42.326768
                      >50K      11.517425       45.558681
Married-spouse-absent <=50K      8.932153       39.368732
                      >50K      12.032258       45.225806
Never-married         <=50K      9.881698       36.756590
                      >50K      12.534043       46.674468
Separated             <=50K      9.174112       39.217640
                      >50K      12.166667       46.212121
Widowed               <=50K      8.987952       33.599732
                      >50K      10.962500       42.100000
```

A trend that's seen in the above pivot table is that for the marital status groups that have at one point been married or are still currently married differ by a small amount of years in their mean age for the income groups, except for the Married-spouse-absent. The <= 50k group of the Married-spouse-absent marital status has a mean age of 40 years old, whereas the > 50k group has a mean age of 48 years old

[44]:
```python
print("Done by Brandon Cabrera")
occupation_pivot_table = pd.pivot_table(data= adult_census_data, index =
 ['occupation', 'income'], values= ['age', 'education.num', 'capital.gain',
 'capital.loss', 'hours.per.week'])
occupation_pivot_table
```

```
Done by Brandon Cabrera
```

[44]:
```
                               age  capital.gain  capital.loss  \
occupation        income
Adm-clerical      <=50K   36.031958    138.317096     50.753025
                  >50K    43.299197   2819.082329    119.753012
Armed-Forces      <=50K   28.250000      0.000000      0.000000
                  >50K    46.000000      0.000000   1887.000000
Craft-repair      <=50K   37.592569    148.671685     67.058616
                  >50K    43.735683   2407.403084    153.394273
Exec-managerial   <=50K   39.628224    184.769830     59.030170
                  >50K    44.893650   4307.764068    224.303562
Farming-fishing   <=50K   40.487414    266.659039     43.516018
                  >50K    47.060870   3070.678261    214.469565
Handlers-cleaners <=50K   31.385951    112.342541     36.377269
```

```
                  >50K    43.240964  2483.746988   163.939759
Machine-op-inspct <=50K   37.038350   155.248693    45.747240
                  >50K    42.297959  1507.987755   148.293878
Other-service     <=50K   34.628896    78.926948    32.992857
                  >50K    41.371212  2579.871212   127.439394
Priv-house-serv   <=50K   42.000000   115.929577    22.507042
                  >50K    47.000000 25236.000000     0.000000
Prof-specialty    <=50K   37.911540   193.944320    66.916031
                  >50K    43.600221  5821.582551   221.925456
Protective-serv   <=50K   37.688940   247.887097    46.822581
                  >50K    41.480952  1676.061905   145.323810
Sales             <=50K   34.802984   135.007651    62.429610
                  >50K    44.358763  4471.389691   198.073196
Tech-support      <=50K   34.399054   194.793375    54.121451
                  >50K    43.140288  1747.528777   199.089928
Transport-moving  <=50K   39.166800   131.960096    65.486832
                  >50K    44.517241  1936.366771   150.689655

                        education.num  hours.per.week
occupation        income
Adm-clerical      <=50K     10.013962       37.054918
                  >50K      10.716867       40.839357
Armed-Forces      <=50K      9.625000       40.750000
                  >50K      14.000000       40.000000
Craft-repair      <=50K      8.914478       41.612108
                  >50K       9.817181       44.656388
Exec-managerial   <=50K     10.825304       42.760097
                  >50K      12.089830       47.308209
Farming-fishing   <=50K      8.431350       46.041190
                  >50K      10.008696       54.208696
Handlers-cleaners <=50K      8.444357       37.581689
                  >50K       9.277108       42.349398
Machine-op-inspct <=50K      8.350959       40.336432
                  >50K       9.351020       43.310204
Other-service     <=50K      8.720455       34.250000
                  >50K      10.136364       42.901515
Priv-house-serv   <=50K      7.183099       32.781690
                  >50K      13.000000       35.000000
Prof-specialty    <=50K     12.365963       40.071846
                  >50K      13.536720       45.207068
Protective-serv   <=50K      9.845622       41.525346
                  >50K      10.900000       45.576190
Sales             <=50K      9.902448       38.276970
                  >50K      11.364948       47.463918
Tech-support      <=50K     10.839117       38.597792
                  >50K      11.258993       41.471223
Transport-moving  <=50K      8.636073       43.619314
```

```
>50K           9.206897        48.699060
```

An intersting thing to to note from the above pivot table is that none of the income groups for Armed-Forces have any capital gain and the amount of hours per week are almost the same.

[37]:
```python
print("Done by Brandon Cabrera")
relationship_pivot_table = pd.pivot_table(data= adult_census_data, index =␣
 ↪['relationship', 'income'], values= ['age', 'education.num', 'capital.gain',␣
 ↪'capital.loss', 'hours.per.week'])
relationship_pivot_table
```

```
Done by Brandon Cabrera
```

[37]:
```
                                 age  capital.gain  capital.loss  education.num  \
relationship   income
Husband        <=50K   42.131191    206.296285     62.477889       9.355248
               >50K    44.561719   3691.779010    200.874274      11.527558
Not-in-family  <=50K   37.327973    138.764305     65.160220      10.144865
               >50K    42.701094   5940.450790    164.340219      12.262454
Other-relative <=50K   32.853630    129.375878     40.624122       8.679157
               >50K    42.000000   2804.428571    398.428571      10.800000
Own-child      <=50K   25.028169     75.630622     37.754884       9.504998
               >50K    36.046875   6102.859375    129.859375      11.156250
Unmarried      <=50K   39.948983    123.621874     32.652884       9.528843
               >50K    45.779343   5411.131455    150.173709      11.868545
Wife           <=50K   39.028090    282.980337     53.853933       9.567416
               >50K    40.789625   2980.096542    179.279539      11.475504

                       hours.per.week
relationship   income
Husband        <=50K        43.003096
               >50K         46.434407
Not-in-family  <=50K        40.380559
               >50K         46.972053
Other-relative <=50K        37.135831
               >50K         42.828571
Own-child      <=50K        33.208996
               >50K         43.281250
Unmarried      <=50K        38.950984
               >50K         46.201878
Wife           <=50K        36.810393
               >50K         38.466859
```

For all of the relationship groups, the > 50k group has made a higher average capital gain amount.

[38]:
```python
print("Done by Brandon Cabrera")
race_pivot_table = pd.pivot_table(data= adult_census_data, index = ['race',␣
 ↪'income'], values= ['age', 'education.num', 'capital.gain', 'capital.loss',␣
 ↪'hours.per.week'])
```

```python
race_pivot_table
```

```
Done by Brandon Cabrera
```

[38]:

```
                                age  capital.gain  capital.loss  \
race               income
Amer-Indian-Eskimo <=50K  36.376984    203.535714     22.234127
                   >50K   39.411765   4045.647059    147.823529
Asian-Pac-Islander <=50K  36.151468    118.278207     48.755796
                   >50K   42.500000   4398.750000    203.677419
Black              <=50K  36.989392    107.908201     40.806610
                   >50K   43.696721   3931.745902    159.806011
Other              <=50K  32.780952     81.719048     46.338095
                   >50K   41.809524  10850.000000     89.857143
White              <=50K  36.619723    155.210014     55.719860
                   >50K   44.055271   3899.515865    195.754642

                          education.num  hours.per.week
race               income
Amer-Indian-Eskimo <=50K       9.123016       39.781746
                   >50K       11.088235       45.205882
Asian-Pac-Islander <=50K      10.496136       38.925811
                   >50K       12.407258       44.608871
Black              <=50K       9.306814       37.798450
                   >50K       11.030055       44.540984
Other              <=50K       8.400000       39.633333
                   >50K       11.523810       44.904762
White              <=50K       9.661307       39.553053
                   >50K       11.611054       45.813715
```

The race with the highest mean age for the > 50k group, which despite having the most amount of people who are making > 50k. The races with fewer representation in the dataset have younger mean ages for their > 50k group.

[39]:

```python
print("Done by Brandon Cabrera")
sex_pivot_table = pd.pivot_table(data= adult_census_data, index = ['sex',␣
↪'income'], values= ['age', 'education.num', 'capital.gain', 'capital.loss',␣
↪'hours.per.week'])
sex_pivot_table
```

```
Done by Brandon Cabrera
```

[39]:

```
                     age  capital.gain  capital.loss  education.num  \
sex    income
Female <=50K   36.231719    119.394348     46.251557       9.878777
       >50K    41.964928   4084.820144    175.451439      11.812950
Male   <=50K   36.841390    167.183352     57.909754       9.474328
       >50K    44.305816   3912.098186    196.932145      11.570513
```

```
                hours.per.week
sex    income
Female <=50K          36.423645
       >50K           40.897482
Male   <=50K          41.162042
       >50K           46.542683
```

The above pivot table allows me to answer the analysis question #9. For males who make > 50k, the average age is 44 years old, rounding to the nearest whole number. For females who make > 50k, the average age is 42 years old, rounding to the nearest whole number. On a side note, both males and females in the <= 50k group have the same average age of 36 without rounding, which is opposite of what we see with the > 50k group of females and males.

[40]:
```python
print("Done by Brandon Cabrera")
native_country_pivot_table = pd.pivot_table(data= adult_census_data, index =␣
 ↪['native.country', 'income'], values= ['age', 'education.num', 'capital.
 ↪gain', 'capital.loss', 'hours.per.week'])
native_country_pivot_table
```

```
Done by Brandon Cabrera
```

[40]:
```
                              age  capital.gain  capital.loss  education.num  \
native.country income
Cambodia       <=50K    37.272727    543.545455    170.545455       7.727273
               >50K     41.428571   1935.714286      0.000000      10.285714
Canada         <=50K    40.098592     70.605634    168.070423      10.239437
               >50K     44.305556   4659.583333    105.250000      11.527778
China          <=50K    41.270833    119.041667    108.187500      10.354167
…                             …           …            …            …
United-States  >50K     44.000429   3965.694353    194.689207      11.586276
Vietnam        <=50K    33.203390    252.406780     99.135593       9.508475
               >50K     35.400000   5873.600000      0.000000       9.600000
Yugoslavia     <=50K    38.000000      0.000000      0.000000       9.700000
               >50K     40.166667    926.000000      0.000000      10.333333

                       hours.per.week
native.country income
Cambodia       <=50K        41.545455
               >50K         40.000000
Canada         <=50K        38.704225
               >50K         46.944444
China          <=50K        38.541667
…                                 …
United-States  >50K         45.750536
Vietnam        <=50K        38.152542
               >50K         39.200000
Yugoslavia     <=50K        41.600000
               >50K         49.500000
```

```
[80 rows x 5 columns]
```

Thailand's > 50k group has the highest average hours worked per week with 58 hours per week!

8 Testing Hypothesis

Now that we have answered our analysis questions let's do some hypothesis test for some of the observations we had for the questions to see if they are statistcally significant and not by chance

Our first hypothesis test will help to confirm whether or not our observation for analysis question #1 is not by chance.

Let:

μ_0: means hour per week for the > 50k group

μ_1: mean hours per week for the <= 50k group

Null Hypothesis: Both groups have the same average amount of hours worked per week, $\mu_0 = \mu_1$

Alternate Hypothesis: The groups don't have the same average amount of hours worked per week, $\mu_0 \neq \mu_1$

For this, we will use a Two-Sample Student T-Test:

- Test whether two independent samples are significantly different
- Assumptions:
  - Observations in each sample are independent and identically distributed (iid).
  - Observations in each sample are normally distributed.
  - Observations in each sample have the same variance.

[41]:
```python
from scipy.stats import ttest_ind
print("Done by Brandon Cabrera")
less_than_equal_to_50k_group = adult_census_data[adult_census_data["binary_income_over_$50k"] == 0]["hours.per.week"]
greater_than_50k_group  = adult_census_data[adult_census_data["binary_income_over_$50k"] == 1]["hours.per.week"]
stat, p = ttest_ind(less_than_equal_to_50k_group, greater_than_50k_group)
if p > 0.05:
  print("Fail to reject null hypothesis")
else:
  print("Reject null hypothesis, there is evidence that the groups don't have the same average amount of hours worked per week")
```

```
Done by Brandon Cabrera
Reject null hypothesis, there is evidence that the groups don't have the same
average amount of hours worked per week
```

We were able to reject the null hypothesis, meaning that the differnce in the average hours worked per week for the two income groups is statistically significant. Our observation of the two groups having different means for the hours worked per week is likely to not be by chance.

Our second hypothesis test will be for the analysis question #9 is not by chance.

Let:

μ_0: mean age for males a part of the > 50k group

μ_1: mean age for females a part of the > 50k group

Null Hypothesis: Both groups are the same age, $\mu_0 = \mu_1$

Alternate Hypothesis: The groups don't share the same age, $\mu_0 \neq \mu_1$

For this, we will use a Two-Sample Student T-Test:

- Test whether two independent samples are significantly different
- Assumptions:
  - Observations in each sample are independent and identically distributed (iid).
  - Observations in each sample are normally distributed.
  - Observations in each sample have the same variance.

[42]:
```
print("Done by Brandon Cabrera")
female_group = adult_census_data[(adult_census_data['binary_income_over_$50k']␣
↪== 1) & (adult_census_data['sex'] == 'Female')]['age']
male_group  = adult_census_data[(adult_census_data['binary_income_over_$50k']␣
↪== 1) & (adult_census_data['sex'] == 'Male')]['age']
stat, p = ttest_ind(female_group, male_group)
if p > 0.05:
  print("Fail to reject null hypothesis")
else:
  print("Reject null hypothesis, there is evidence that the groups don't share␣
↪the same mean age")
```

```
Done by Brandon Cabrera
Reject null hypothesis, there is evidence that the groups don't share the same
mean age
```

We were able to reject the null hypothesis. This means that our observation for analysis question #9 is in line with the hypothesis test since we found that the average age for women a part of the > 50k group was different than the average age of males a part of the > 50k group.

9 Conclusions

9.0.1 Analysis question #1

Q: What was the average number of hours worked for a person who made > 50k, and what was the average number of hours worked for a person who made $<=$ to 50k?

A: The average number of hours worked for a person who made > 50k is 45.7 hours worked per week. The average number of hours worked for a person who made <= 50k is 39.3 hours worked per week.

9.0.2 Analysis question #2

Q: For a person whose highest education level is only high school, who makes > 50k, if any, what is the average number of hours worked?

A: For a person whose highest education level is HS-grad and is a part of the > 50k group, the average age is 45 years old, rounding to the nearest whole number.

9.0.3 Analysis question #3

Q: What is the average education level for a person making > 50k and what is the average education level for a person making <= 50k?

A: The average education number for a person making > 50k is 12 if we round up to the nearest number, which is equivalent to Assoc-acdm in terms of education level. The average education number for a person making <= 50k is 10, meaning they have some college.

9.0.4 Analysis question #4

Q: What is the correlation between capital gain and whether or not a person makes over 50k?

A: The correlation between capital gain and a person making over > 50k is 0.221, indicating a weak positive relationship. This makes sense since not everyone who is making money from investments might be making a profit compared to their losses, or the money made isn't much. The correlation between capital gain and a person making <= 50k is -0.221 indicating, a weak negative relationship.

9.0.5 Analysis question #5

Q: What marital status has the most people making over 50k, and what marital status has the most people making less than or equal to 50k?

A: The marital status with the most amount of people making > 50k is married-civ-spouse. The marital status with the most amount of people making <= 50k is Never-married.

9.0.6 Analysis question #6

Q: What numerical column has the highest amount of correlation, in terms of magnitude, with whether or not a person made > 50k and whether they make <= 50k?

A: The column with the highest amount of correlation, in terms of magnitude, for both binary columns is education.num with a value of 0.335. This is a weak relationship, indicating that as a person's education level becomes higher, they are more likely to make >50k. If we look at it from the perspective of making <= 50k, -0.335 indicates it indicates that as a person's education level becomes higher than they are less likely to make <= 50k.

9.0.7 Analysis question #7

Q: What workclass has the most people making <= 50k, and what work class has the most people making > 50k?

A: The private workclass has the most amount of people making > 50k, as well as the most amount of people making less <= 50k.

9.0.8 Analysis question #8

Q: Do women or men tend to make > 50k more than the other, and do women or men tend to make <= 50k?

A: The sex with the most amount of people who make > 50k and the most of people who make <= 50k is the male sex.

9.0.9 Analysis question #9

Q: What is the average age of men who make > 50k, and what is the average age of women who make > 50k?

A: For males who make > 50k, the average age is 44 years old, rounding to the nearest whole number. For females who make > 50k, the average age is 42 years old, rounding to the nearest whole number.

9.0.10 Analysis question #10

Q: Which race tends to make > 50k, more than the other races, and what race tends to make <= 50k more than the other races?

A: The race with the most amount of people making > 50k is the white race, and it's also the race with the most amount of people making <= 50k. It's worth noting that I am considering only the frequency and not the percentages, which would be a fairer assessment of which race tends to make more.